

COMMENTS OF THE ELECTRONIC PRIVACY INFORMATION CENTER

to the

COMPTROLLER OF THE CURRENCY; FEDERAL RESERVE SYSTEM; FEDERAL DEPOSIT INSURANCE CORPORATION; CONSUMER FINANCIAL PROTECTION BUREAU; NATIONAL CREDIT UNION ADMINISTRATION

Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning

86 FR 16837

July 1, 2021

In response to the request for comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning, published on March 31, 2021,¹ by the Comptroller of the Currency; the Federal Reserve System; the Federal Deposit Insurance Corporation; the Consumer Financial Protection Bureau; and the National Credit Union Administration (“financial agencies”), the Electronic Privacy Information Center (“EPIC”) submits the following comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning.

EPIC is a public interest research center in Washington, D.C., established in 1994 to focus public attention on emerging privacy and related human rights issues, and to protect privacy, the First Amendment, and constitutional values.² As part of the AI and Human Rights project, EPIC has long advocated for fairness and transparency in the use of algorithms that impact individuals.

¹ *Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning*, [Comptroller of the Currency](#), the [Federal Reserve System](#), the [Federal Deposit Insurance Corporation](#), the [Consumer Financial Protection Bureau](#), and the [National Credit Union Administration](#), 86 FR 16837 (Mar. 31, 2021)

<https://www.federalregister.gov/documents/2021/03/31/2021-06607/request-for-information-and-comment-on-financial-institutions-use-of-artificial-intelligence>

² EPIC, *About EPIC* (2019), <https://epic.org/epic/about.html>.

Specifically, EPIC has pushed for the adoption of Universal Guidelines for AI to establish requirements for trustworthy algorithms and for increased reporting, testing, and validation to ensure transparency and oversight of these systems.³ EPIC has successfully pushed for the public release of reports evaluating risk assessment tools and other AI systems that have been developed for government and law enforcement purposes.⁴ EPIC also recently submitted comments to the National Security Commission on Artificial Intelligence, the U.S. Office of Science and Technology Policy, the European Commission, the U.S. Office of Management and Budget urging these institutions to develop regulatory frameworks that ensure the protection of individual rights.⁵ EPIC publishes the *AI Policy Sourcebook*, one of the first global reference books on AI policy.⁶

EPIC recommends that the agencies incorporate the tenets for AI policy-making expressed in the AI Principles of the Organisation of Economic Cooperation and Development (“OECD AI Principles”), of which the United States is among 42 national signatories.⁷ EPIC also recommends implementation of the Universal Guidelines for AI (“UGAI”), a framework for AI governance based on the protection of human rights, which was established at the 2018 Public Voice meeting in

³ See e.g. EPIC v. DOJ (D.C. Cir.) (18-5307), EPIC v CPB, EPIC v. DHS, FOIA requests, <https://epic.org/foia/doj/criminal-justice-algorithms/>; EPIC, *Liberty at Risk*, epic.org/libertyatrisk (2020).

⁴ See *Id.* and EPIC, *EPIC v. DHS (FAST Program)* <https://epic.org/foia/dhs/fast/>.

⁵ Comments of EPIC, *Solicitation of Written Comments by the National Security Commission on Artificial Intelligence*, 85 Fed. Reg. 32,055, National Security Commission on Artificial Intelligence (Sep. 30, 2020) <https://epic.org/apa/comments/EPIC-comments-to-NSCAI-093020.pdf>; Comments of EPIC, *Request for Comments on a Draft Memorandum to the Heads of Executive Departments and Agencies, “Guidance for Regulation of Artificial Intelligence Applications,”* 85 Fed. Reg. 1825, Office of Management and Budget (Mar. 13, 2020)

<https://epic.org/apa/comments/EPIC-OMB-AI-MAR2020.pdf>; Comments of EPIC, *Request for Feedback in Parallel with the White Paper on Fundamental Rights*, European Commission Fundamental Rights Policy Unit (May 29, 2020)

<https://epic.org/apa/comments/EPIC-EU-Commission-AI-Comments-May2020.pdf>; Comments of EPIC, *Proposal for a legal act of the European Parliament and the Council laying down requirements for Artificial Intelligence*, European Commission (Sep. 10, 2020) <https://epic.org/apa/comments/EPIC-EU-Commission-AI-Sep2020.pdf> .

⁶ *EPIC AI Policy Sourcebook 2019* (EPIC 2019), <https://epic.org/bookstore/ai2019/>.

⁷ Organisation for Economic Co-operation and Development, *OECD Principles on AI* (May 2019) <https://www.oecd.org/going-digital/ai/principles/>.

Brussels, Belgium.⁸ The Universal Guidelines have been endorsed by more than 250 experts and 60 organizations in 40 countries.⁹ The UGAI comprise twelve principles:

1. Right to Transparency.
2. Right to Human Determination.
3. Identification Obligation.
4. Fairness Obligation.
5. Assessment and Accountability Obligation.
6. Accuracy, Reliability, and Validity Obligations.
7. Data Quality Obligation.
8. Public Safety Obligation.
9. Cybersecurity Obligation.
10. Prohibition on Secret Profiling.
11. Prohibition on Unitary Scoring.
12. Termination Obligation.¹⁰

EPIC submits these comments to the leading financial regulatory agencies in the United States to urge that the agencies act in accordance with their consumer protection mandates and create rules that rightfully scrutinize AI systems that are being deployed in the financial sector. Specifically, the agencies should promulgate rules addressing the myriad equity and fairness issues that the adoption of these AI systems raise, establish regulations that address the current lack of accountability and compliance of AI tools with consumer financial protection obligations, and eliminate safe harbors that incentivize opaque and unfair AI systems.

In January 2020, the Office of Management and Budget, in coordination with the Office of Science and Technology and Policy, released its “Guidance for Regulation of Artificial Intelligence Applications.” The OMB AI Guidance, which applies to “all Federal agencies,” incorporates many of the precepts of the OECD AI Principles. The OMB AI Guidance lays out ten “Principles for the Stewardship of AI Applications”:

⁸ *Universal Guidelines for Artificial Intelligence*, The Public Voice (Oct. 23, 2018) [hereinafter *Universal Guidelines*], <https://thepublicvoice.org/ai-universal-guidelines/>

⁹ *Id.*

¹⁰ *Id.*

1. Public Trust in AI
2. Public Participation.
3. Scientific Integrity and Information Quality.
4. Risk Assessment and Management.
5. Benefits and Costs.
6. Flexibility.
7. Fairness and Non-Discrimination.
8. Disclosure and Transparency.
9. Safety and Security.
10. Interagency Coordination.¹¹

OMB warns in the guidance that “AI applications could pose risks to privacy, individual rights, autonomy, and civil liberties that must be carefully assessed and appropriately addressed. Its continued adoption and acceptance will depend significantly on public trust and validation.”¹² The OMB further instructs that “[w]hen considering regulations or policies related to AI applications, agencies should ... protec[t] ... privacy, civil liberties, and other American values, including the principles of freedom, human rights, the rule of law, and respect for intellectual property.”¹³ In promulgating regulations to protect consumers, EPIC reminds the agencies of their obligation to regulate AI in accordance with the OMB guidance above.

As the financial agencies explain in the Request for Comment, there are both benefits and risks to AI used in the financial sector. While use of AI in this sector might be beneficial where it can increase efficiency for financial entities, improve fraud detection, and expand credit access for some communities, it poses significant risks. The financial agencies are uniquely equipped to identify and prohibit the use of systems that illegally inhibit credit access in a discriminatory manner or fail to meet the legally required explainability under ECOA for adverse actions. The agencies

¹¹ Draft Memorandum from Russell T. Vought, Acting Dir., Office of Mgmt. & Budget to Heads of Exec. Dep’t and Agencies at 3-6 (Jan. 7, 2020), <https://www.whitehouse.gov/wp-content/uploads/2020/01/Draft-OMB-Memo-on-Regulation-of-AI-1-7-19.pdf>.

¹² *Id.* at 3.

¹³ *Id.* at 1.

should use their power to determine what systems are being used, what systems should be allowed to be used, and what systems impermissibly disadvantage the public.

There are significant concerns about the use of AI systems including lack of explainability and increased data collection and usage despite bias and inaccuracies. In addition to the concerns of appropriateness and accuracy for data, systems that use dynamic updating¹⁴ collect additional data that may not be adequately vetted for bias. This dynamic updating and use of additional data may also not be clear to the consumer or financial entity that relies on the output of the tool. This opacity disadvantages consumers by further limiting their understanding of what personal data is collected and what tools are used on them.

EPIC urges the financial agencies to establish data protection limits to benefit financial consumers, require transparency and accountability about financial actors using AI, and modernize enforcement of civil rights laws.

Question 2: How do financial institutions use post-hoc methods to assist in evaluating conceptual soundness? How common are these methods? Are there limitations of these methods (whether to explain an AI approach's overall operation or to explain a specific prediction or categorization)? If so, please provide details on such limitations.

Establishing appropriate metrics to evaluate conceptual soundness is important for facilitating oversight of AI systems and improving fairness. The financial sector has a widely documented history of redlining and other racially discriminatory practices.¹⁵ Deploying AI systems,

¹⁴ Dynamic Updating: Some AI approaches have the capacity to update on their own, sometimes without human interaction, often known as dynamic updating. Monitoring and tracking an AI approach that evolves on its own can present challenges in review and validation, particularly when a change in external circumstances (e.g., economic downturns and financial crises) may cause inputs to vary materially from the original training data. Dynamic updating techniques can produce changes that range from minor adjustments to existing elements of a model to the introduction of entirely new elements. *Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning*, supra note 1 at 18640.

¹⁵ Mehrsa Baradaran, *The Color of Money: Black Banks and the Racial Wealth Gap* (2017); Alexander Butler et al, *Racial Discrimination in the Auto Loan Market* (March 31, 2021) available at SSRN: <http://ssrn.com/abstract=3301009>; Ethan Cohen-Cole, *Credit Card Redlining* (February 9, 2009), FRB of Boston Quantitative Analysis Unit Working Paper No. QAU08-1, <https://ssrn.com/abstract=1098403>;

which draw on historical data, into a field with this discriminatory history increases the risk of embedding disparate outcomes. In this area, moreso than others, it is important to ensure that testing, documentation, transparency, and accountability are implemented to identify and correct for systemic biases.¹⁶ Accordingly, both prior and concurring conceptual soundness evaluations should be required if a system is adopted. This would help financial agencies get a comprehensive picture of the AI systems that are being adopted by entities and regulate according to the level of risk. Both the status quo and the idea of solely post-hoc evaluations puts the regulators and therefore consumers at a disadvantage for protection.

Prior to deployment of a tool, conceptual soundness must be extensively thought out, documented, tested, and published by an independent body. During and after deployment, these same principles of completeness and transparency are essential for the use of any tools. The National Institute of Standards and Technology’s Principles for AI Explainability provide a useful guide for any financial actor to fulfill for a given system – that a system can “deliver evidence or reasons for all outputs;” that a system can “provide explanations that are understandable to individual users;” that the explanation “correctly reflects the system’s process for generating the output;” and that the system “only operates under conditions for which it was designed or when the system reaches a sufficient confidence in the output.”¹⁷

In order to operationalize these principles and apply them to protecting consumers under the Equal Credit Opportunity Act and other consumer protection provisions, the agencies must dictate

¹⁶ See, e.g. Robert Bartlett, Adair Morse, Richard Stanton, Nancy Wallace, *Consumer-lending Discrimination in the Fintech Era*, National Bureau of Economic Research (June 2019) available at <http://www.nber.org/papers/w25943>

“We find that lenders charge Latinx/African-American borrowers 7.9 and 3.6 basis points more for purchase and refinance mortgages respectively, costing them \$765M in aggregate per year in extra interest.”

¹⁷ P. Jonathon Phillips et. al, *Four Principles of Explainable Artificial Intelligence*, National Institute of Standards and Technology (Aug. 2020) available at <https://www.nist.gov/system/files/documents/2020/08/17/NIST%20Explainable%20AI%20Draft%20NISTIR8312%20%281%29.pdf>

appropriate conditions and purposes of a given system; require consistent affirmations that operations of the tool are aligned with this commitment; require transparency around the factors in a model, the justifications for the use of those factors, documentation of disparate impact based on protected classes in Regulation B, and mitigating factors.

There must be evaluation of a system for conceptual soundness both prior to adoption and regularly while being used, including evaluation of the surrounding infrastructure and potential points of inaccuracy or bias that can facilitate compliance with equal protection regulations. Algorithmic Impact Assessments are one tool the financial agencies can require. Algorithmic Impact Assessments vary in specific content, but they guide users through questions about why they're adopting a given system, what capabilities their system holds, how explainable it is, what kind of decisions it helps make, how much intervention is involved, how sensitive their data is, how synthesized the data is, who the adopting agency is consulting about the adoption, mitigating measures, procedural fairness, and more.¹⁸ For these assessments to be effective, they must be mandatory, robust, public, and part of an infrastructure that legitimizes it. An AI Now report analyzing how Algorithmic Impact Assessments can be operationalized has outlined a robust process of requiring Pre-acquisition review; Initial agency disclosure requirements; Comment period; Due process challenge period; and renewal for any system adopted.¹⁹

One example of an Algorithmic Impact Assessment system already in wide use is the one deployed by the Canadian Digital Service.²⁰ Questions used in the Canadian tool include prompts to evaluate the stakes of decisions the system in question makes, vulnerability of subjects, and whether

¹⁸ Government of Canada, *Algorithmic Impact Assessment* (last visited Jan. 29, 2021) available at <https://open.canada.ca/aia-eia-js/?lang=en>.

¹⁹ Dillon Reisman, Jason Schultz, Kate Crawford, Meredith Whitaker, *Algorithmic Impact Assessments: A practical framework for public agency accountability*, AI Now Institute (April 2018) <https://ainowinstitute.org/aiareport2018.pdf>.

²⁰ Canada Digital Services, *Algorithmic Impact Assessment* (last visited June 9, 2021) <https://open.canada.ca/aia-eia-js/?lang=en>.

it is a predictive risk assessment, and allowing for multiple sectors or categories when describing what functions the system uses.²¹ The Canadian assessment also requires clear delineation of the downstream processes of a system. These involves asking (i) will the system only be used to assist a decision-maker; (ii) will the system be replacing a decision that would otherwise be made by a human; (iii) will the system be replacing human judgment; (iv) whether the system is being used by the same entity that developed it; and (v) consideration and explanation about both economic and environmental impacts.²² Although no comparable assessment system is required by regulation in the United States, there are pending bills at both the state and federal level that would make that assessment process mandatory.²³ The financial agencies should take this opportunity to impose an assessment requirement on all regulated financial entities that use AI systems in the financial sector, and make the results of those assessments available to the public.

Question 4: How do financial institutions using AI manage risks related to data quality and data processing? How, if at all, have control processes or automated data quality routines changed to address the data quality needs of AI? How does risk management for alternative data compare to that of traditional data? Are there any barriers or challenges that data quality and data processing pose for developing, adopting, and managing AI? If so, please provide details on those barriers or challenges.

Developing and implementing AI systems in the lending process poses significant challenges to data quality and data processing. This risk increases with the use of “alternative data” sources in these models. Although touted as more equitable, alternative data sources are significantly more opaque and may have understudied effects on marginalized communities. The use of alternative data also poses significant privacy and surveillance concerns – as data used and created for one purpose is

²¹ *Id.*

²² *Id.*

²³ H.R. 2231, *Algorithmic Accountability Act of 2019* (116th Congress) <https://www.congress.gov/bill/116th-congress/house-bill/2231>; Washington S.B. 5116, *An Act Relating to establishing guidelines for government procurement and use of automated decision systems in order to protect consumers, improve transparency, and create more market predictability* (2021) <https://app.leg.wa.gov/billsummary?BillNumber=5116&Year=2021&Initiative=False>; California AB13, *Public contracts: automated decision systems* (2021), https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=20210220AB13.

then used in an unrelated context that impacts the availability of financial services. A 2020 report from the Student Borrower Protection Center analyzing publicly available information from both Wells Fargo and the financial technology company Upstart showed that borrowers are charged higher rates when the systems use alternative data, such as which college an individual attended. In their analysis, when all else is equal but an applicant attended a community college, Historically Black College or University, or a Hispanic-Serving Institutions:

- Borrowers who take out private loans to pay for college may pay a penalty for attending a community college. Wells Fargo charges a hypothetical community college borrower an additional \$1,134 on a \$10,000 loan when compared to a similarly situated borrower enrolled at a four-year college.
- Borrowers who refinance their student loans through a company using education data may pay a penalty for having attended an HBCU. When refinancing with Upstart, a hypothetical Howard University graduate is charged nearly \$3,499 more over the life of a five-year loan than a similarly situated NYU graduate.
- Borrowers who refinance student loans may pay a penalty for having attended an Hispanic-Serving Institution (HSI). When refinancing with Upstart, a hypothetical graduate who receives a Bachelor's Degree from New Mexico State University, an HSI, is charged at least \$1,724 more over the life of a five-year loan when compared to a similarly situated NYU graduate.²⁴

The increased adoption of AI tools is enabled by a consistent and vast increase in the collection of personal data. With both traditional and alternative data sources, safeguards must be put into place to ensure accuracy and quality of the data. There are currently insufficient protections in place about the collection, maintenance, disclosure, and use of personal data in the financial sector. When personal data is collected and used, the financial agencies must establish rules that limit collection and retention to articulated purpose-driven need, and limit sale, sharing, or other downstream misuse. Analytical tools that aggregate and anonymized data don't pose the same privacy risks as personalized data does, but effects modeling used in AI systems.

²⁴ Student Borrower Protection Center, *Education Redlining Report* (Feb. 2020), available at <https://protectborrowers.org/wp-content/uploads/2020/02/Education-Redlining-Report.pdf>.

Question 12: What are the risks that AI can be biased and/or result in discrimination on prohibited bases? Are there effective ways to reduce risk of discrimination, whether during development, validation, revision, and/or use? What are some of the barriers to or limitations of those methods?

Question 15: The Equal Credit Opportunity Act (ECOA), which is implemented by Regulation B, requires creditors to notify an applicant of the principal reasons for taking adverse action for credit or to provide an applicant a disclosure of the right to request those reasons. What approaches can be used to identify the reasons for taking adverse action on a credit application, when AI is employed? Does Regulation B provide sufficient clarity for the statement of reasons for adverse action when AI is used? If not, please describe in detail any opportunities for clarity.

There are significant risks that use of AI tools can lead to biased results or outright discrimination on prohibited bases. One clear example is a result of the Student Borrower Protection Center report, which led to a Monitorship agreement between Upstart, Student Borrower Protection Center, and NAACP Legal Defense Fund after allegations that their lending model likely violated both the Equal Credit Opportunity Act and fair housing laws.²⁵ Other similar models that could cause disparate impacts not only based on race but also disability, age, housing, and more have not yet been uncovered because of insufficient reporting and documentation. The use of alternative data runs a particular risk of both inaccurate or complete information as well as “the potential for discrimination.”²⁶ The monitorship between Upstart, the NAACP and the Student Borrower Protection Center illustrated specific actions that financial agencies could take to use algorithmic models to identify disparate impacts, root them out, and discourage use of inappropriate models. The agreements include disparate impact testing of “whether a model causes an adverse impact on a

²⁵ *LDF and Student Borrower Protection Center Send Letter to Financial Technology Firm over Equal Credit Opportunity Act and Fair Housing Act Violations*, National Association for the Advancement of Colored people Legal Defense Fund (July 30, 2020) <https://www.naacpldf.org/press-release/ldf-and-student-borrower-protection-center-send-letter-to-financial-technology-firm-over-equal-credit-opportunity-act-and-fair-housing-act-violations/>; *Initial Report of the Independent Monitor Pursuant to agreement by the NAACP Legal Defense and Educational Fund, the Student Borrower Protection Center, and Upstart Network, Inc.*, RelamN Colfax PLLC (Apr. 14, 2021) https://www.relmanlaw.com/media/cases/1088_Upstart%20Initial%20Report%20-%20Final.pdf

²⁶ Brian Kreiswirth, et al., CFPB Blog, “Using alternative data to evaluate creditworthiness,” (Feb. 16, 2017), <https://www.consumerfinance.gov/about-us/blog/using-alternative-data-evaluate-creditworthiness/>; see also Solon Barocas, Andrew Selbst, *Big Data’s Disparate Impact*, 104 Cal. L. Rev. 671 (2016) available at <http://www.californialawreview.org/wp-content/uploads/2016/06/2Barocas-Selbst.pdf>.

protected class; whether the creditor has identified a legitimate business need for the model or variable; and whether a less discriminatory alternative exists.”²⁷

In addition to statistical analysis methods of analyzing adverse impact on protected classes, financial agencies should require entities to dedicate human resources to stringently vet data sources for accuracy and disparate impact, identify gaps in models where meaningful explainability is not available, and communicate with applicants regarding any models being used. In addition to statistical analysis methods of analyzing adverse impact on protected classes, Access to a meaningful explanation of the principal reasons for adverse action is central to Regulation B of the Equal Credit Opportunity Act, making it essential for these resources to be required in addition to statistical analysis methods of analyzing disparate impact. Financial actors must be held responsible for the AI tools they utilize and the agencies must prevent a lower standard for legal compliance simply because a financial entity adopts an automated model. This rule would amount to a safe harbor for tools that obfuscates compliance with important equal protection requirements.

In October 2020, a federal judge struck down a rule that incentivized the use of algorithmic models for lending in fair housing contexts by lowering the burden for lenders that used an opaque algorithmic model and exponentially increasing the plaintiff’s burden in proving disparate impact.²⁸ The rule allowed for a lack of explainability in these models, and EPIC urges the financial agencies not to mirror that rule for the financial sector. In accordance with the Equal Credit Opportunity Act and that precedent, the financial agencies should establish requirements that require proactive disclosures about AI systems used, independent third-party assessments, limited purpose-appropriate

²⁷ NAACP *supra* note 12 at 9.

²⁸ *Massachusetts Fair Housing Center v. United States Department of Housing and Urban Development*, U.S. Dist. Ct. Mass., Civil Action No. 20-11765-MGM (2020), available at <http://lawyersforcivilrights.org/wp-content/uploads/2020/10/Nationwide-PI-Against-HUD.pdf>

data collection and use, and meaningful access to understand decisions and remedy data inaccuracies.

Conclusion

EPIC urges agencies to treat the adoption of AI in lending with skepticism in light of equity and fairness issues. The adoption of AI by financial actors should not be treated as inevitable, and the agencies are uniquely posed to protect consumers through data collection and use limits, reporting and accountability requirements, and bans on certain discriminatory or untested uses of AI.

Respectfully submitted,

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